# Storypoint Problem Exploration - clover

September 3, 2024

## 1 Storypoint Prediction: Problem Exploration

### 1.1 Problem Statement

In modern agile development settings, software is developed through repeated cycles (iterative) and in smaller parts at a time (incremental), allowing for adaptation to changing requirements at any point during a project's life. A project has a number of iterations (e.g. sprints in Scrum). Each iteration requires the completion of a number of user stories, which are a common way for agile teams to express user requirements.

There is thus a need to focus on estimating the effort of completing a single user story at a time rather than the entire project. In fact, it has now become a common practice for agile teams to go through each user story and estimate its "size". Story points are commonly used as a unit of measure for specifying the overall size of a user story.

### 1.2 Problem Formulation

**Input:** A string of length $N$ that contains a story's name and description $C = \{c_1, c_2, c_3, ..., c_n\}$. For each story, a set of text embeddings that contains features $E = \{e_1, e_2, e_3, ..., e_m\}$ extracted from C has been provided.

**Output**: A natural number P associated with the story point of that user story

### 1.3 Dataset Information

**Text Embeddings:** Text embeddings are a way to convert words or phrases from text into a list of numbers, where each number captures a part of the text's meaning. The dataset has been preprocessed and converted into two kinds of text embeddings. You can choose to work with either of them or both: - Doc2Vec: Input strings are transformed into fixed-length vectors of size 128. These vectors capture the semantic meaning of words and their relationships within a document. - Look-upTable: Input strings are transformed into fixed-length vectors of size 2264. These vectors are obtained via transforming each word in the input strings into an identifier number, then padded to the length of the longest sample.

**Dataset Structure & Format:** Storypoint Estimation Dataset is stored in 3 folders labeled *raw data*, *look-up*, and *doc2vec*. Within each folder are 3 CSV files for training, testing, validation. Each csv file has the following columns: - `issuekey` : The unique identifier for a story. - `storypoint`: The correct number of storypoint. - An embedding column (`embedding` or `doc2vec`) contains text embedding vectors. The raw data csv will not have this and instead contain two columns with story `name` and `description`.

## 1.4 Exploration

### 1.4.1 Raw data exploration

[ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.feature_extraction.text import CountVectorizer
```

**Output exploration**

[ ]:
```
# Import raw data from the CSV file

project_name = 'clover'

all_data = pd.concat([pd.read_csv('data/' + project_name + '/' + project_name +
 ↪'_train.csv'),
                      pd.read_csv('data/' + project_name + '/' + project_name +
 ↪'_valid.csv'),
                      pd.read_csv('data/' + project_name + '/' + project_name +
 ↪'_test.csv')])

print('Check the shape of the dataset', all_data.shape)
```

```
Check the shape of the dataset (361, 4)
```

[ ]:
```
all_data.drop(['issuekey'], axis=1, inplace=True)
all_data.head()
```

[ ]:
```
                                              title  \
0                    line coverage data inconsistent
1   surefire classpath incorrect depending jar tes…
2                 message balloon clean snapshot bogus
3       instrumentation done always get two tests run
4   test columns empty projectjs generated via jso…

                                        description  storypoint
0   running idea get inconsistent line branch cove…           2
1   two different applications symptom test cases …           2
2   clean shapshot first optimised test run balloo…           2
3   although instr done still see two tests run co…           1
4   json report generated test fields erroneoustes…           2
```

First, let take a look at the distribution of the story point:

Interpretation of Skewness Values:

- **Skewness > 0**: Right-skewed distribution.
- **Skewness < 0**: Left-skewed distribution.

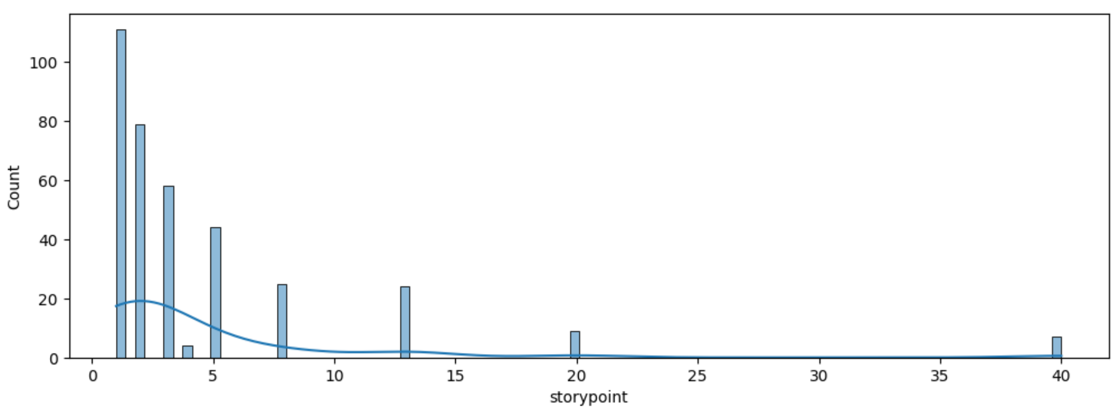
- **Skewness = 0**: Symmetrical distribution (like a normal distribution).

Interpretaion of kurtosis: - **Leptokurtic (Kurtosis > 3)**: The distribution has heavier tails and a sharper peak than the normal distribution. Data points are more likely to produce extreme values. The distribution has a higher peak and fatter tails. - **Platykurtic (Kurtosis < 3)**: The distribution has lighter tails and a flatter peak than the normal distribution. Data are fewer extreme values compared to a normal distribution. - **Mesokurtic (Kurtosis  3)**: The distribution has a similar kurtosis to the normal distribution, indicating a moderate level of outliers.

[ ]:
```
# Draw a histogram of the story points
plt.figure(figsize=(12, 4))
plt.xticks(np.arange(0, max(all_data['storypoint']) + 1, 5))
sns.histplot(all_data['storypoint'], bins=100, kde=True)

print('Skewness:', all_data['storypoint'].skew())
print('Kurtosis:', all_data['storypoint'].kurt())
```

```
Skewness: 3.6594420968073123
Kurtosis: 15.933910666176914
```




[ ]:
```
tmp = pd.concat([all_data['storypoint'].value_counts(),
                 all_data['storypoint'].value_counts() / all_data.shape[0] *
↪100],
                axis=1, keys=['Counts', 'Percentage (%)'])
tmp.head(20)
```

[ ]:

| | Counts | Percentage (%) |
|---|---|---|
| storypoint | | |
| 1 | 111 | 30.747922 |
| 2 | 79 | 21.883657 |
| 3 | 58 | 16.066482 |
| 5 | 44 | 12.188366 |
| 8 | 25 | 6.925208 |
| 13 | 24 | 6.648199 |

```
20                 9       2.493075
40                 7       1.939058
4                  4       1.108033
```

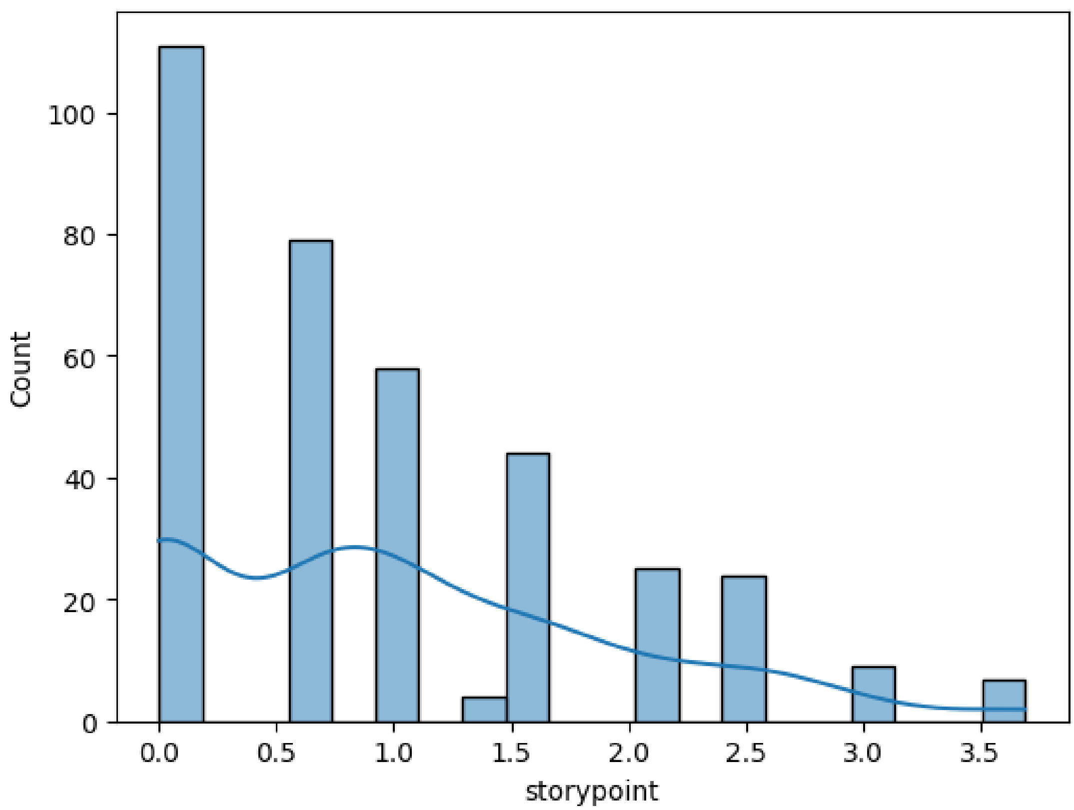
At the first sight, this data is bad. Then take a look at the statistic values, this data is even worse. Its distribution of the label is **right-skewed** and **leptokurtis**. This means if we use this to train model, the right side of the data can be the outliers and make the models become unsuable.

I will try 2 solutions: - Use log-scale on the label - Remove all the examples with label greater than a threshold (20, 30 or 40)

The first solution: logarithm magic

[ ]:
```
sns.histplot(np.log(all_data['storypoint']), bins=20, kde=True)
```

[ ]:
```
<Axes: xlabel='storypoint', ylabel='Count'>
```



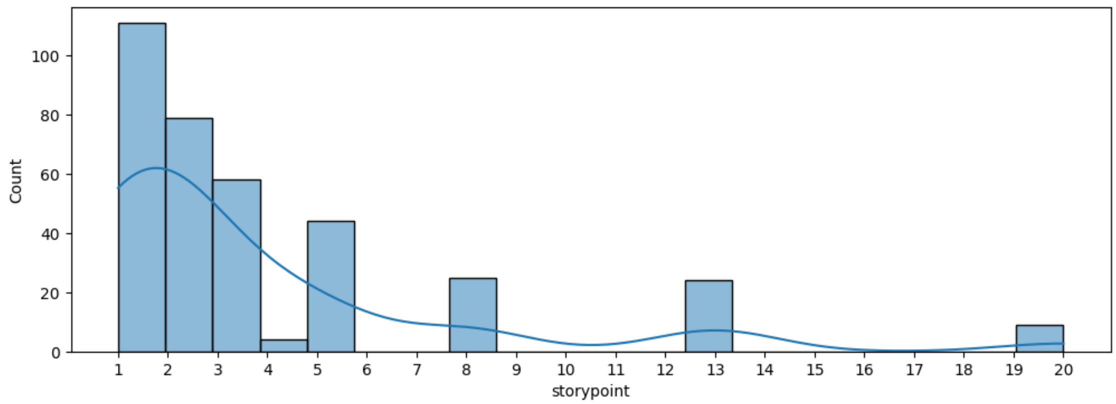

The second solution: Dismantle and Cleave

[ ]:
```
threshold = 20 # This threshold means that we will take all the examples with␣
↪story points less than or equal to 20

new_data = all_data[all_data['storypoint'] <= threshold]
```

```
plt.figure(figsize=(12, 4))
plt.xticks(np.arange(0, max(new_data['storypoint']) + 1, 1))
sns.histplot(new_data['storypoint'], bins=threshold, kde=True)
print('Fitered percentage: ', round(1 - new_data.shape[0] / all_data.shape[0],
    2) * 100, '%')
```

```
Fitered percentage:  2.0 %
```




**Input exploration** The input of this problem is 2 texts: title and description. First we will find some statistics:

```
[ ]: title_lengths = all_data['title'].apply(lambda x: len(x.split(' ')))
print('Title analysis:')
print('   - Mean length:', round(title_lengths.mean()))
print('   - Min length:', title_lengths.min())
print('   - Max length:', title_lengths.max())

description_lengths = all_data['description'].apply(lambda x: len(x.split(' '))
    if type(x) != float else 0)
print('Description analysis:')
print('   - Mean length:', round(description_lengths.mean()))
print('   - Min length:', description_lengths.min())
print('   - Max length:', description_lengths.max())
```

```
Title analysis:
   - Mean length: 6
   - Min length: 2
   - Max length: 13
Description analysis:
   - Mean length: 49
   - Min length: 0
   - Max length: 673
```

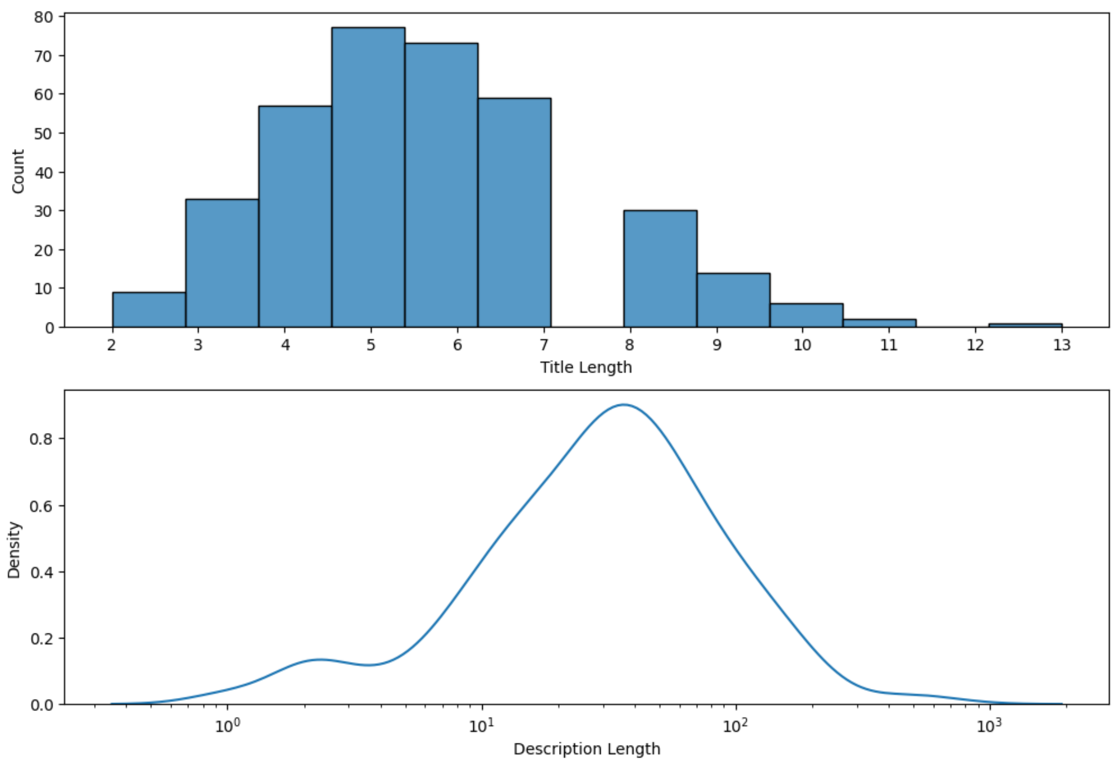
Plot the histogram of the title length and KDE of the description length (exclude 0):

```
[ ]: plt.figure(figsize=(12, 8))

     plt.subplot(2, 1, 1)
     plt.xticks(np.arange(0, max(title_lengths) + 1, 1))
     plt.xlabel('Title Length')
     sns.histplot(title_lengths, bins=max(title_lengths))

     plt.subplot(2, 1, 2)
     plt.xlabel('Description Length')
     plt.xscale('log')
     sns.kdeplot(description_lengths[description_lengths > 0])
```

```
[ ]: <Axes: xlabel='Description Length', ylabel='Density'>
```




I think we should check the correlation between title length and description length:

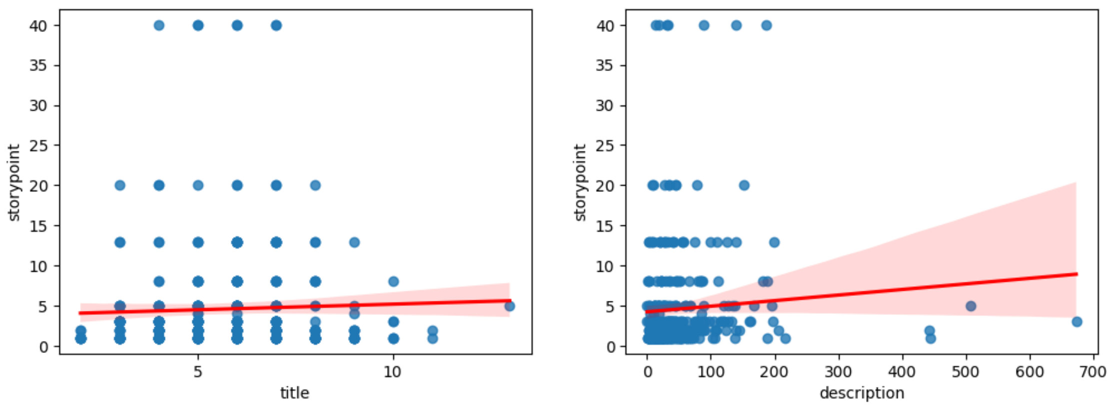
```
[ ]: plt.figure(figsize=(12, 4))

     plt.subplot(1, 2, 1)
     plt.xticks(np.arange(0, max(all_data['title'].apply(lambda x: len(x.split('␣
       ↪'))))) + 1, 5))
     sns.regplot(x=all_data['title'].apply(lambda x : len(x.split(' '))),
                 y=all_data['storypoint'],
```

```
            line_kws={'color': 'red'})

plt.subplot(1, 2, 2)
sns.regplot(x=all_data['description'].apply(lambda x : len(x.split(' ')) if type(x) != float else 0),
            y=all_data['storypoint'],
            line_kws={'color': 'red'})
```

[ ]:
```
<Axes: xlabel='description', ylabel='storypoint'>
```




Maybe a small corelation between storypoint and title

Let dive deeper in the input:

Title analysis:

[ ]:
```
count_vectorizer = CountVectorizer()
count_vectorizer.fit(all_data['title'])

dictionary = pd.DataFrame(list(count_vectorizer.vocabulary_.items()), columns=['word', 'frequency'])
dictionary.sort_values(by='frequency', ascending=False, inplace=True)
print(dictionary.shape)
dictionary.head(10)
```

```
(849, 2)
```

[ ]:

| | word | frequency |
|---|---|---|
| 827 | zerowidth | 848 |
| 458 | xml | 847 |
| 729 | wrong | 846 |
| 116 | write | 845 |
| 469 | works | 844 |
| 118 | working | 843 |

```
463   workaround        842
57          work        841
538      wizards        840
248         wins        839
```

Description analysis:

```
[ ]: count_vectorizer = CountVectorizer()
     count_vectorizer.fit(all_data[all_data['description'].isnull() ==␣
      ↪False]['description'])

     dictionary = pd.DataFrame(list(count_vectorizer.vocabulary_.items()),␣
      ↪columns=['word', 'frequency'])
     dictionary.sort_values(by='frequency', ascending=False, inplace=True)
     print(dictionary.shape)
     dictionary.head(20)
```

```
(4203, 2)
```

[ ]:

| | word | frequency |
|---|---|---|
| 1066 | zip | 4202 |
| 1784 | zim | 4201 |
| 4122 | zerowidth | 4200 |
| 2725 | zero | 4199 |
| 1733 | youre | 4198 |
| 2335 | youd | 4197 |
| 982 | yet | 4196 |
| 1540 | yes | 4195 |
| 1712 | yellow | 4194 |
| 1008 | years | 4193 |
| 4130 | xyzjavaunexpected | 4192 |
| 2390 | xyz | 4191 |
| 3888 | xxxxxxxxxx | 4190 |
| 3220 | xxxx | 4189 |
| 1162 | xxx | 4188 |
| 728 | xml | 4187 |
| 3505 | xception | 4186 |
| 1052 | xbootclasspath | 4185 |
| 1422 | wwwatlassiancom | 4184 |
| 3526 | wsdljava | 4183 |

Yet I don't find any thing special about the words in input except so many things are bad.

### 1.4.2 Solving strategies

My first intuitation in this problem is that the hard part is not on the algorithm we use, it is on the **embedding** part. Therefore, in case the given embedded datasets work not properly, I will use a better embedding method which is **Bidirectional Encoder Representations from Transformers (BERT)**. Also, I will try an old way to embedding the text too: **Bag of words**.

In conclusion, I will have 4 ways to embed the text: - doc2vec (already available) - Look up (already available) - Bag Of Words - BERT

About algorithm, I will try all the regression algorithm that may give a good result:

- Ridge Regressor
- Support Vector Regressor
- Random Forest Regressor
- Gradient Boosting
- XGBoost
- Lightgbm
- Blended

Maybe, we can change the problem to the classification problem with 100 labels (desparation confirmed). In the classification problem, I will use: - Support Vector Classifier - Softmax Regression (Multinomial Logistic Regression) - Random Forest - Adaboost - XGBoost

Thanks to the libaries, the implementation of all the algorithm shrinks to its minimum form.

At last, there is still a situation that all of mentioned model don't give a good result. This gamble is thrilling (hopeless).

*"But would you lose?"*

Nah, I'd win.